

JAVIER DUARTE (UCSD)
SNOWMASS EF02
HIGGS+FLAVOR MEETING
SEPTEMBER 3, 2020

# JET FLAVOR TAGGING FOR HIGGS PHYSICS

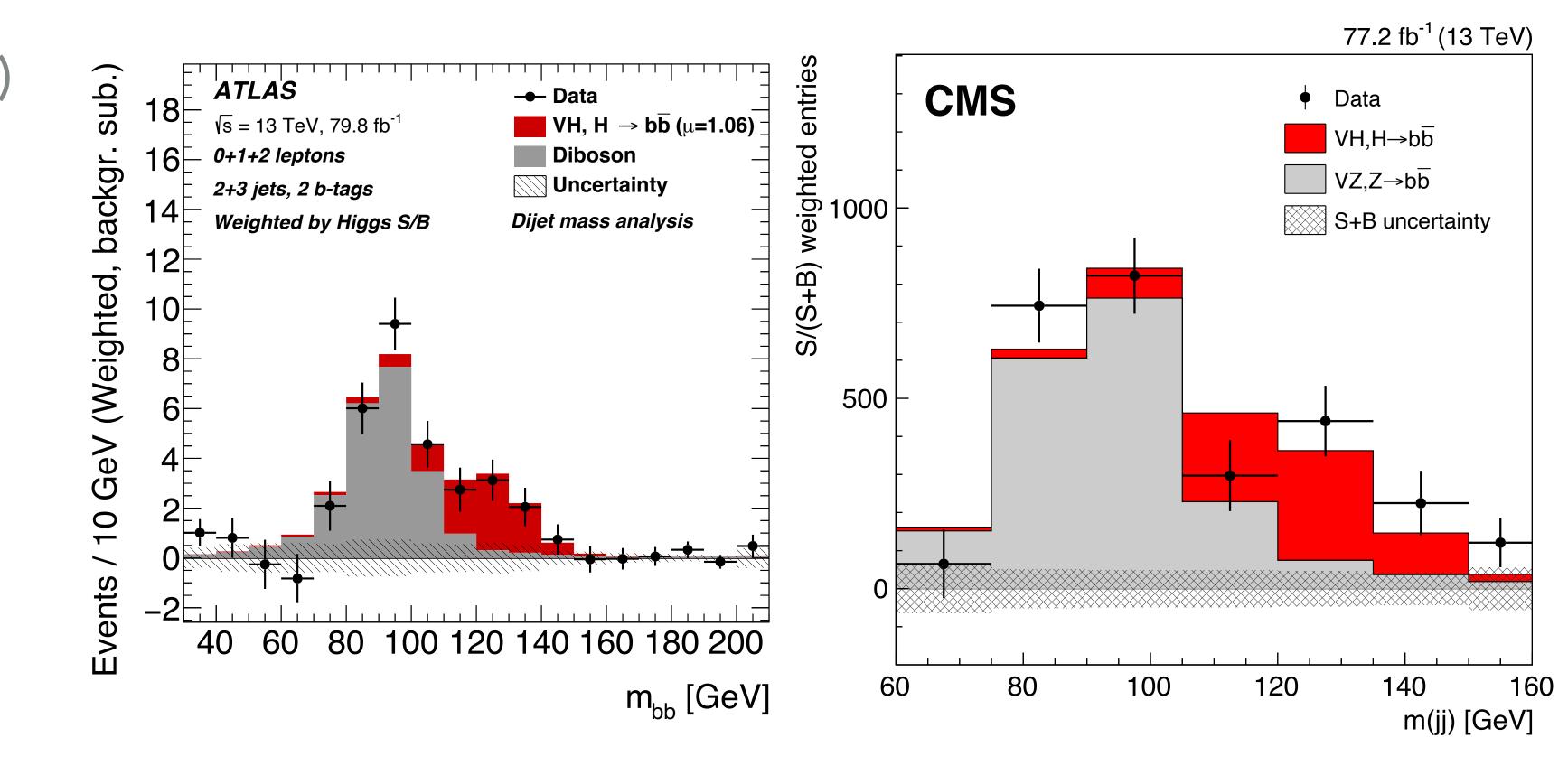
- Introduction
- Overview of flavor tagging
- Recent developments (ML)
- Use in analysis
- Experimental considerations
- Use in the trigger
- Summary and outlook

Note: Apologies for CMS-centric details

#### INTRODUCTION

- Heavy flavor jet tagging is an important aspect of Higgs searches
  - Techniques have been "ML"-based for a while [arXiv:1607.08633]
    - e.g. in NN taggers in LEP [arXiv:hep-ex/0311003], D0 [arXiv:1002.4224], MV1 at ATLAS [arXiv:1512.01094] in ATLAS and cMVA, CSVv2 in CMS [arXiv:1712.07158]
- Recently played a role in the observation of VH(bb)
- Techniques are still evolving
- 2nd generation (charm)more challenging

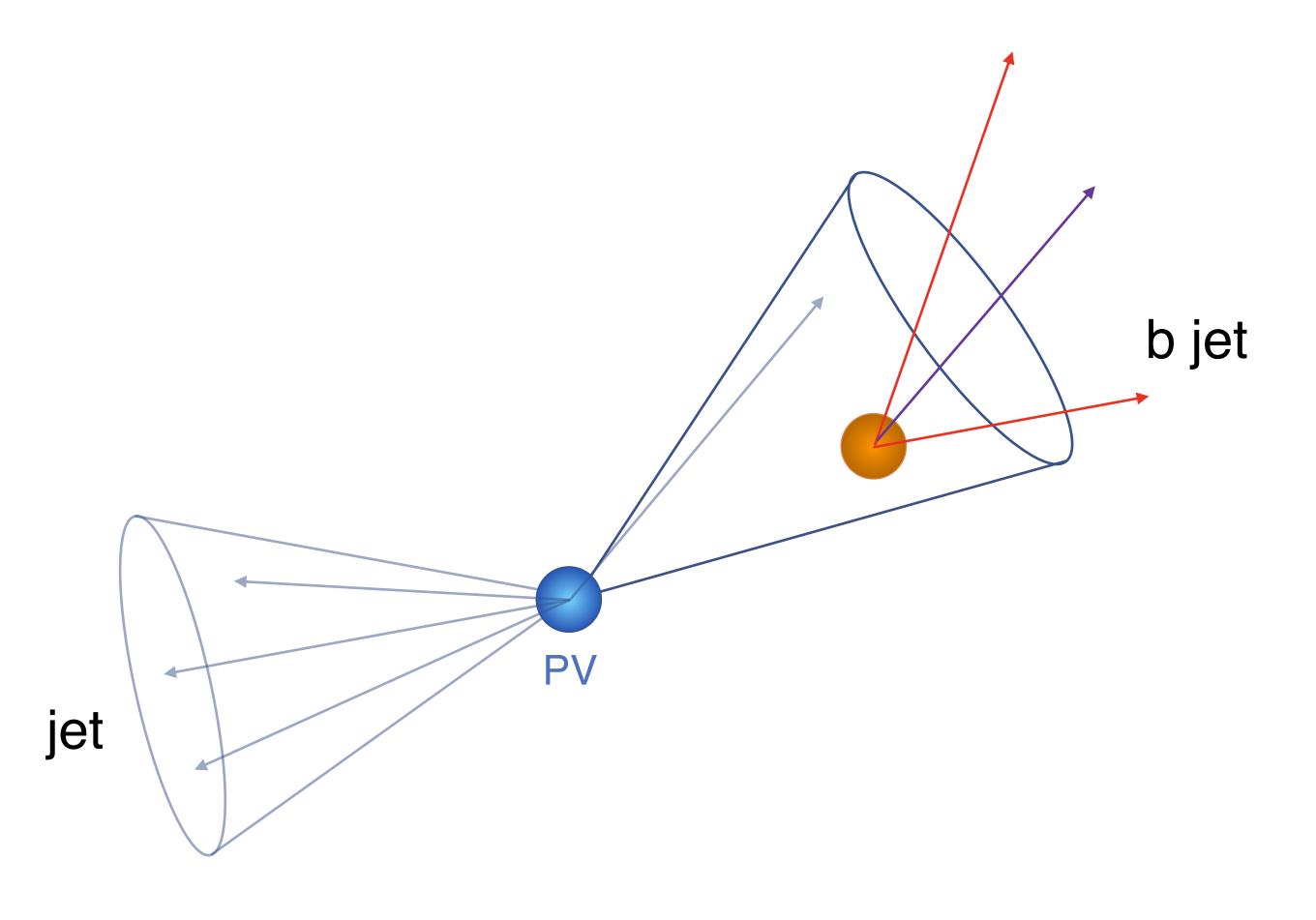
H decay	BF
bb	58.2%
CC	2.9%



b jet PV jet

anti- $k_T$ R=0.4

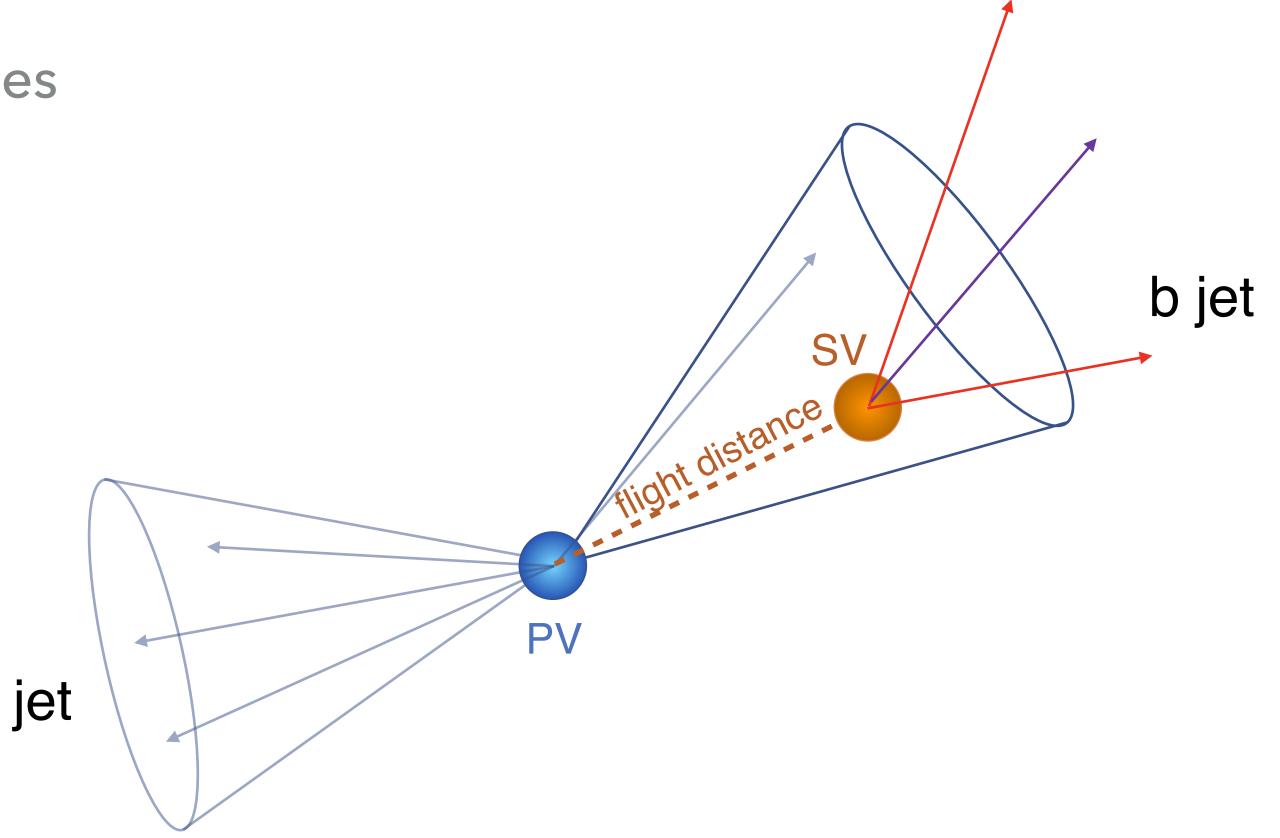
Handles:



anti-k<sub>T</sub> R=0.4

Handles:

secondary vertices

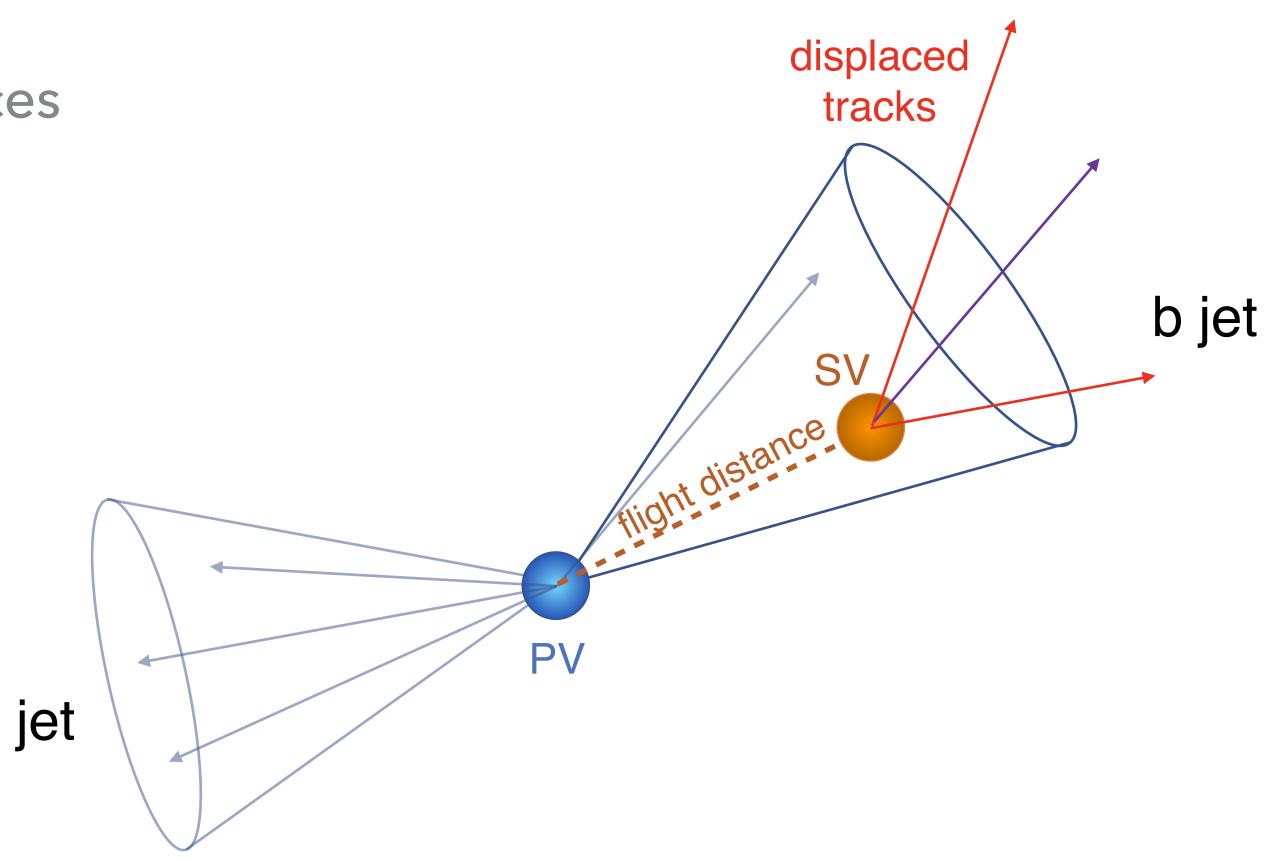


anti- $k_T$ R=0.4

Handles:

secondary vertices

displaced tracks



anti-k<sub>T</sub>

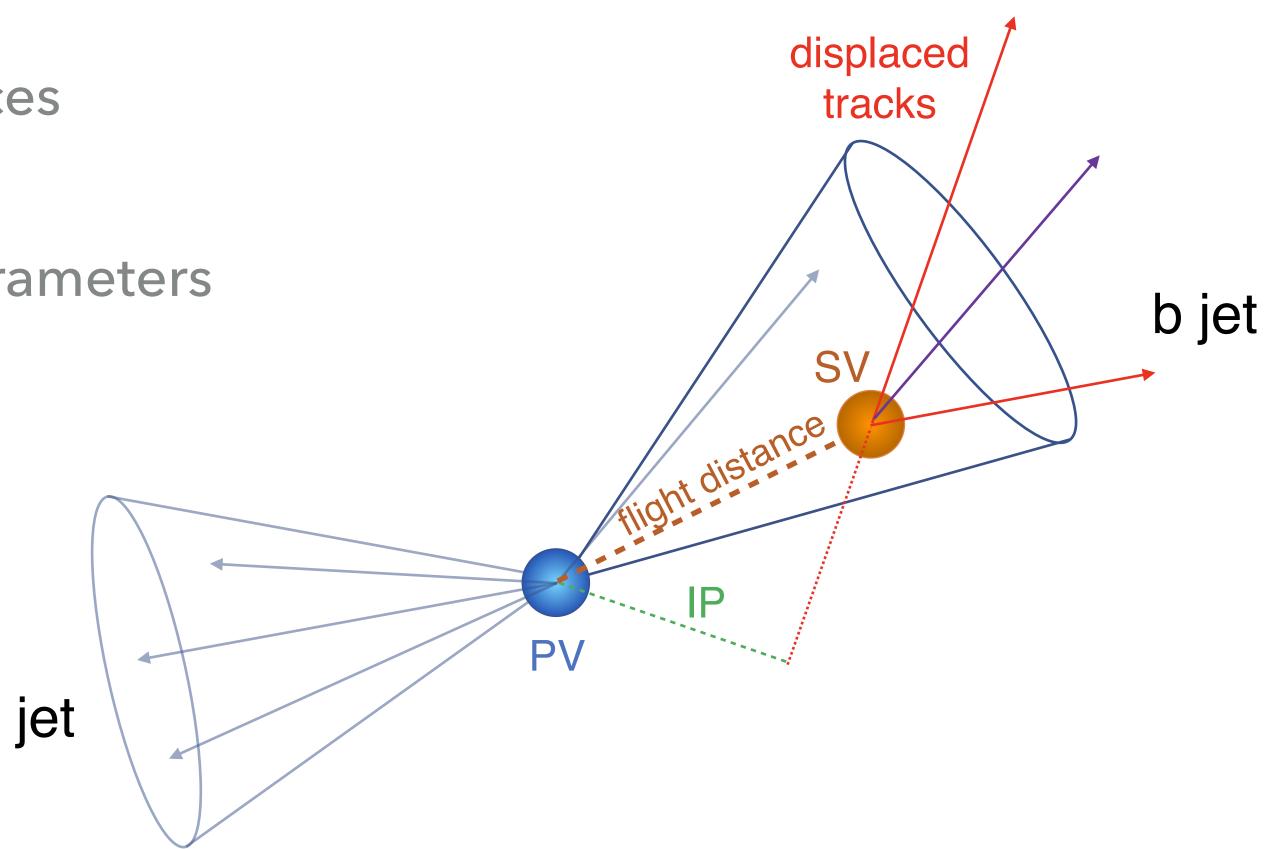
R = 0.4

Handles:

secondary vertices

displaced tracks

large impact parameters



anti-k<sub>T</sub>

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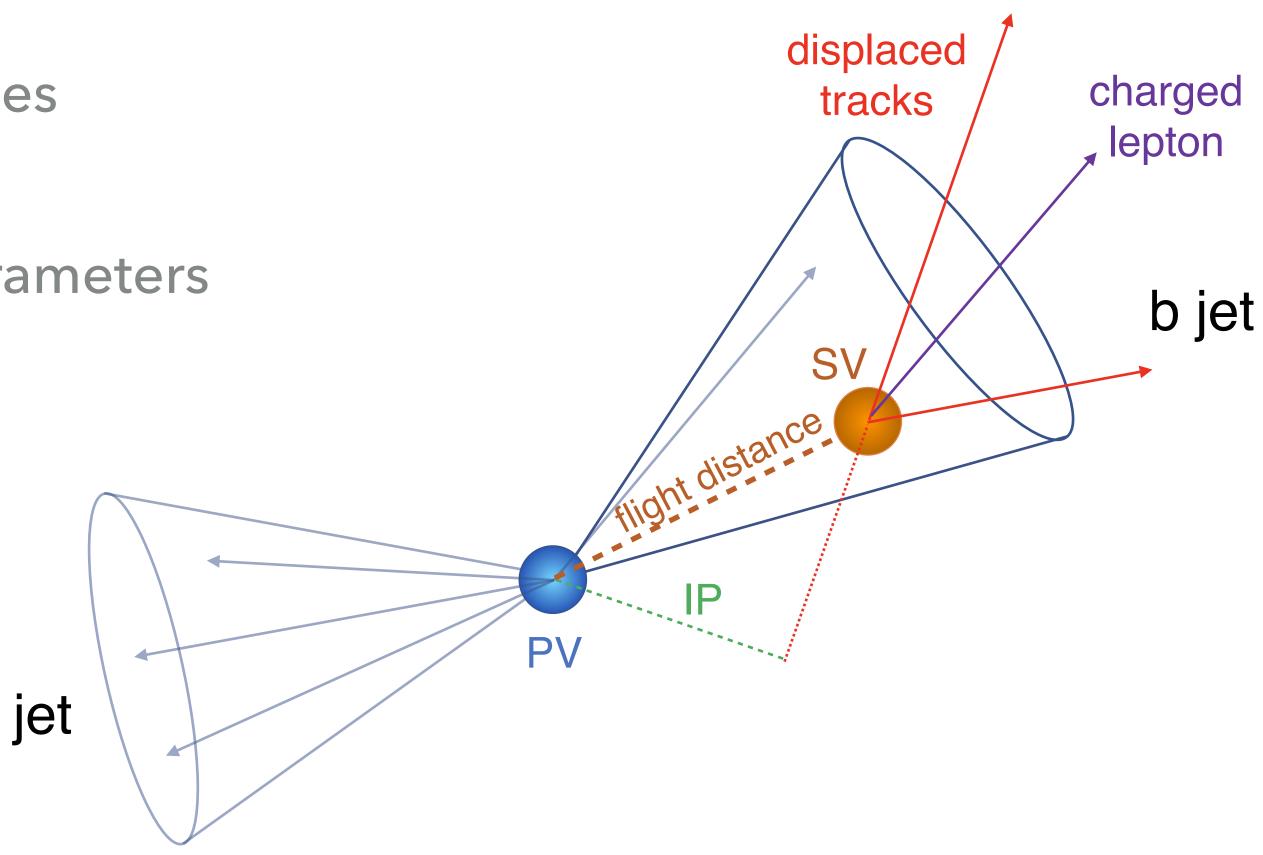
Handles:

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displaced tracks

large impact parameters

soft leptons



anti-k<sub>T</sub>

R = 0.4

# HIGGS (DOUBLE-B) TAGGING

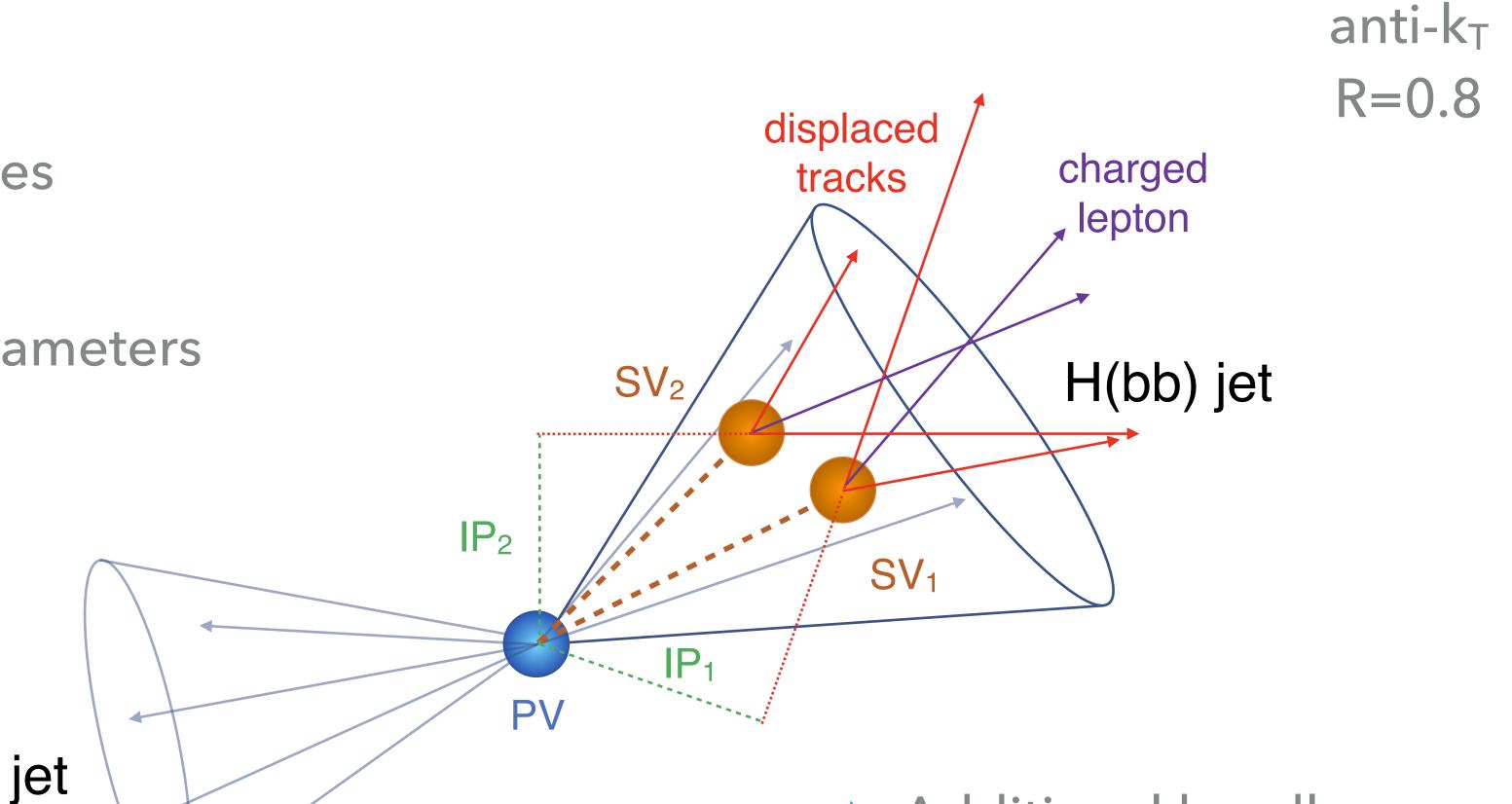
Handles:

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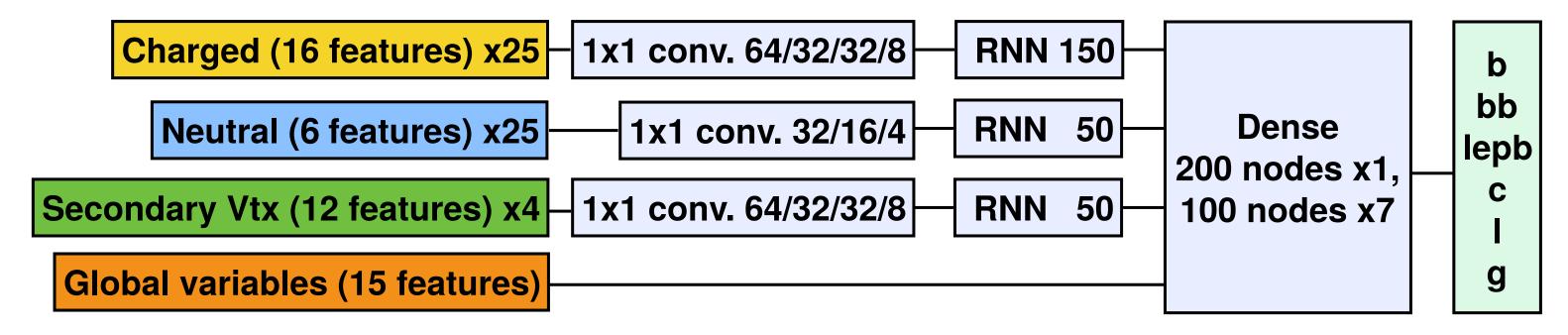
large impact parameters

soft leptons

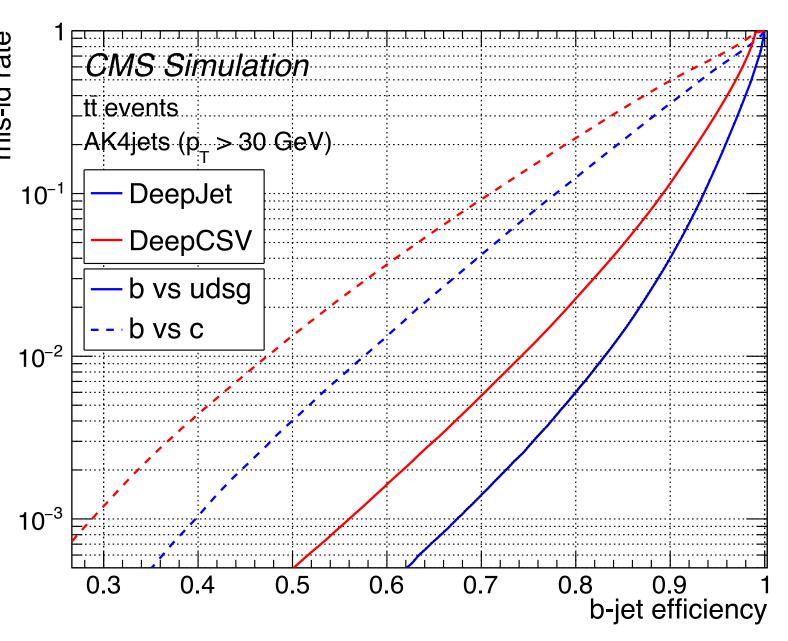


- Additional handles:
  - Relative position of SVs

DeepJet [dlps\_2017\_10, CMS-DP-2018-058] considers low-level charged and neutral particle, secondary vertex, and global features to categorize the flavor of AK4 jets using a mixture of recurrent and dense neural networks

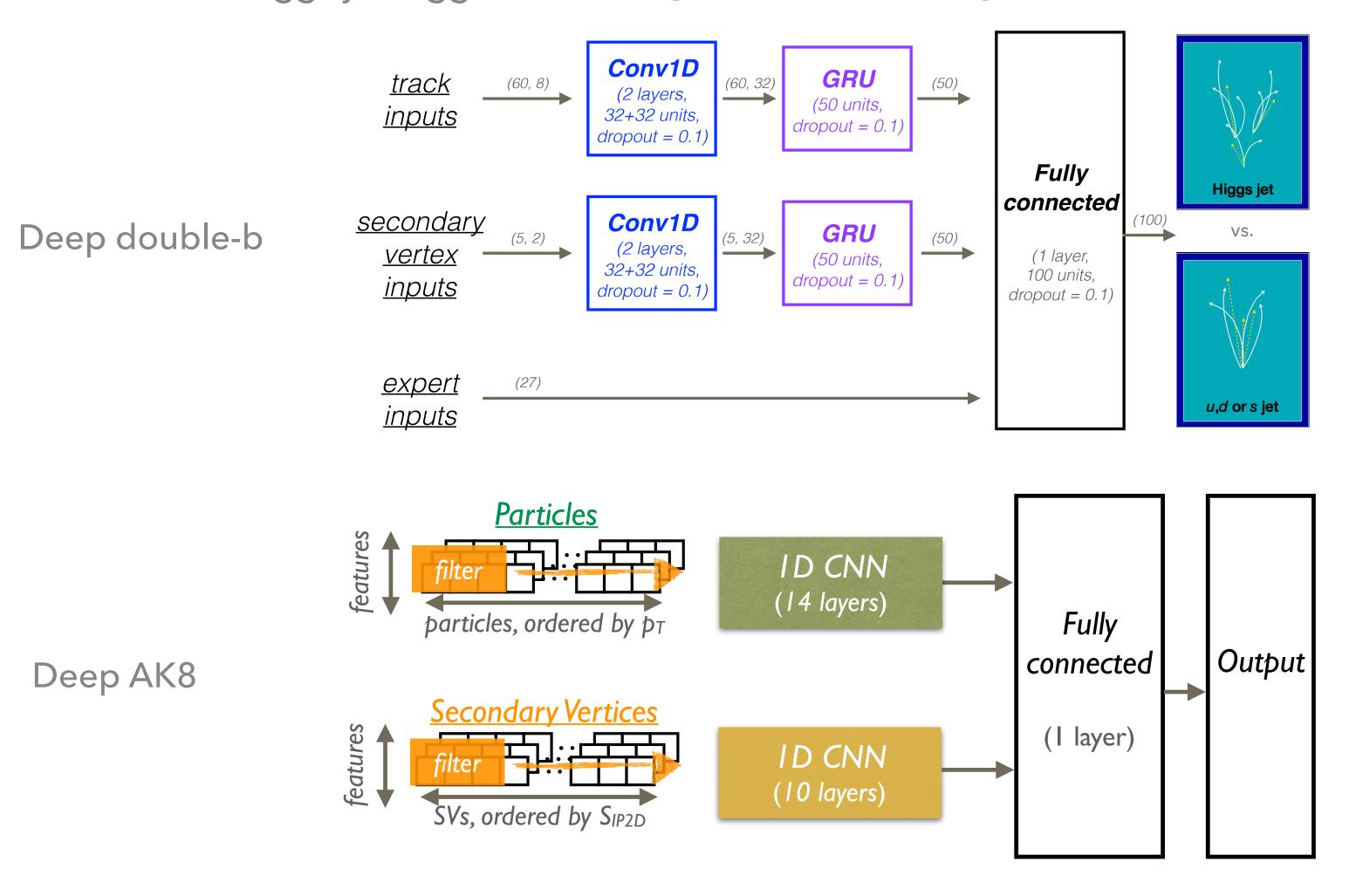


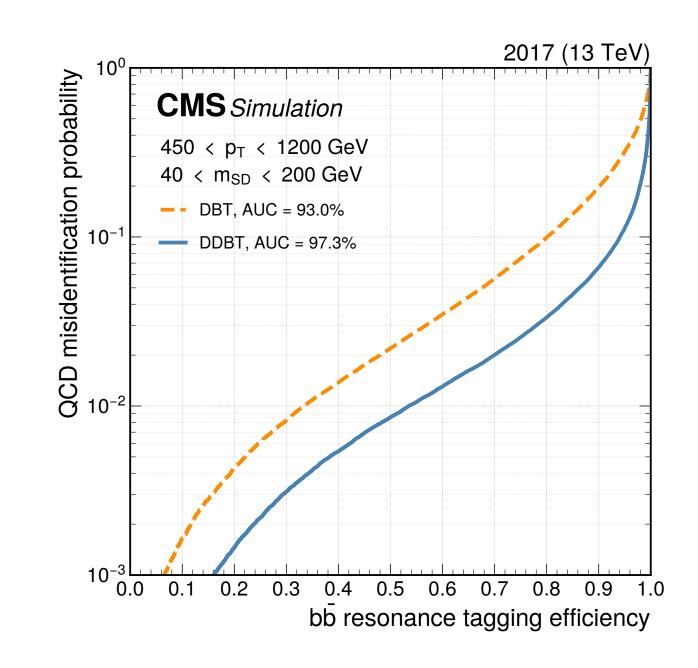
- Large improvement over previous methods:
  - DeepJet: 84% b-jet efficiency for 1% mis-id
  - DeepCSV: 75% b-jet efficiency

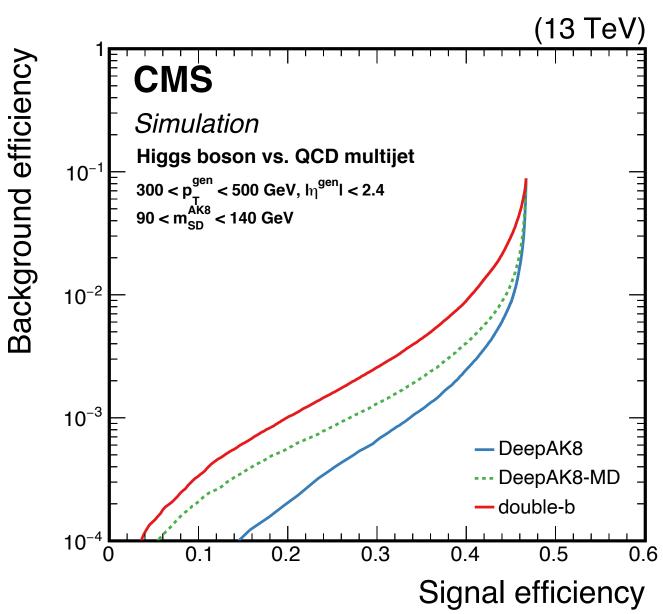


# DEEP DOUBLE-X, DEEP AK8 TAGGERS

- Deep double-x and deep AK8 in CMS: similar approach using low-level features now applied to large-radius jets
  - $\triangleright$  50-70% H(bb) efficiency for 1% mis-id (depending on m<sub>SD</sub>, p<sub>T</sub> range)
- Related: Higgs jet tagger in ATLAS [arXiv:1906.11005]

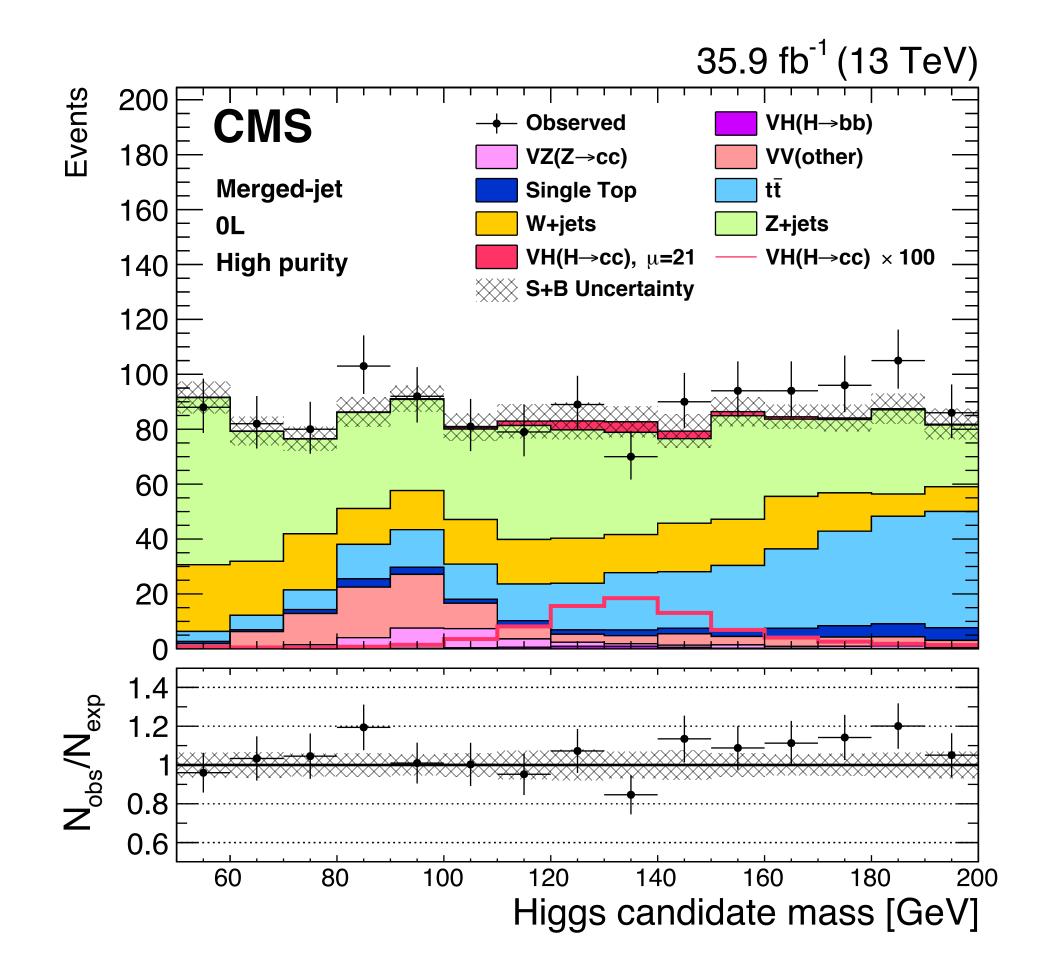


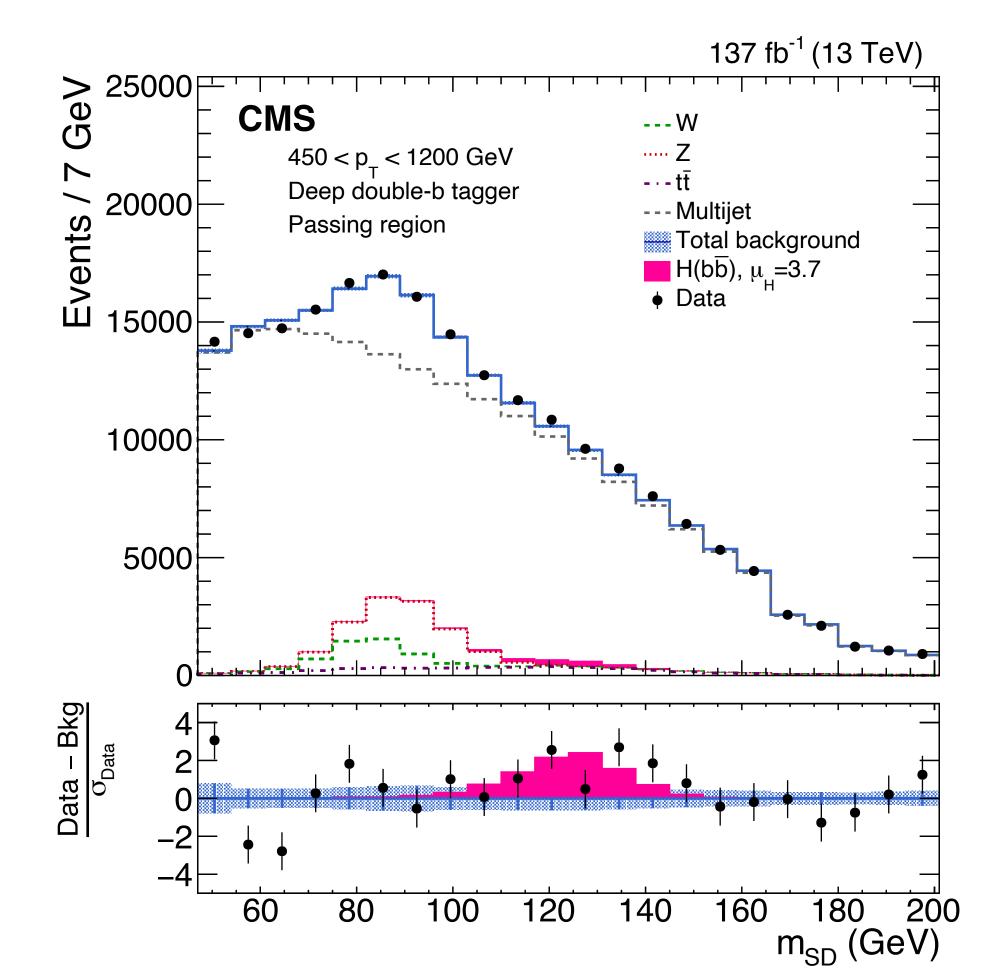




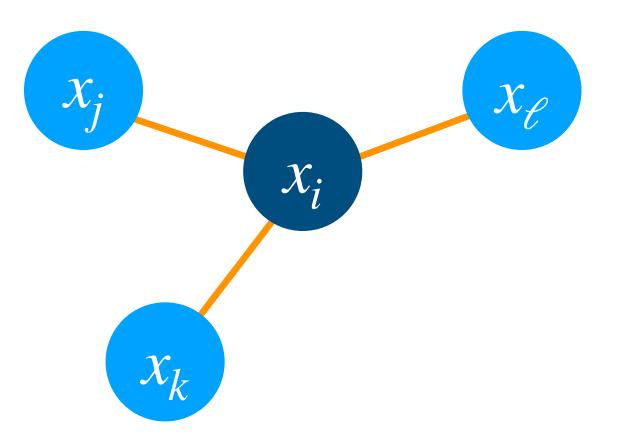
#### **USE IN PHYSICS ANALYSIS**

- New tagging (deep AK8 and deep double-b) methods used in CMS VH(cc) and ggH(bb) searches
  - These searches made possible because of these methods!

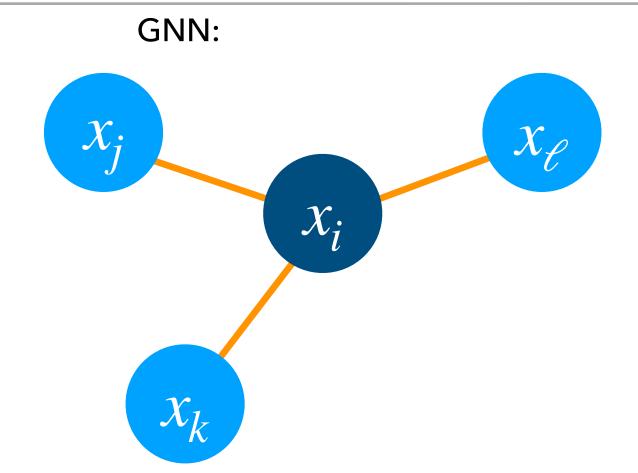




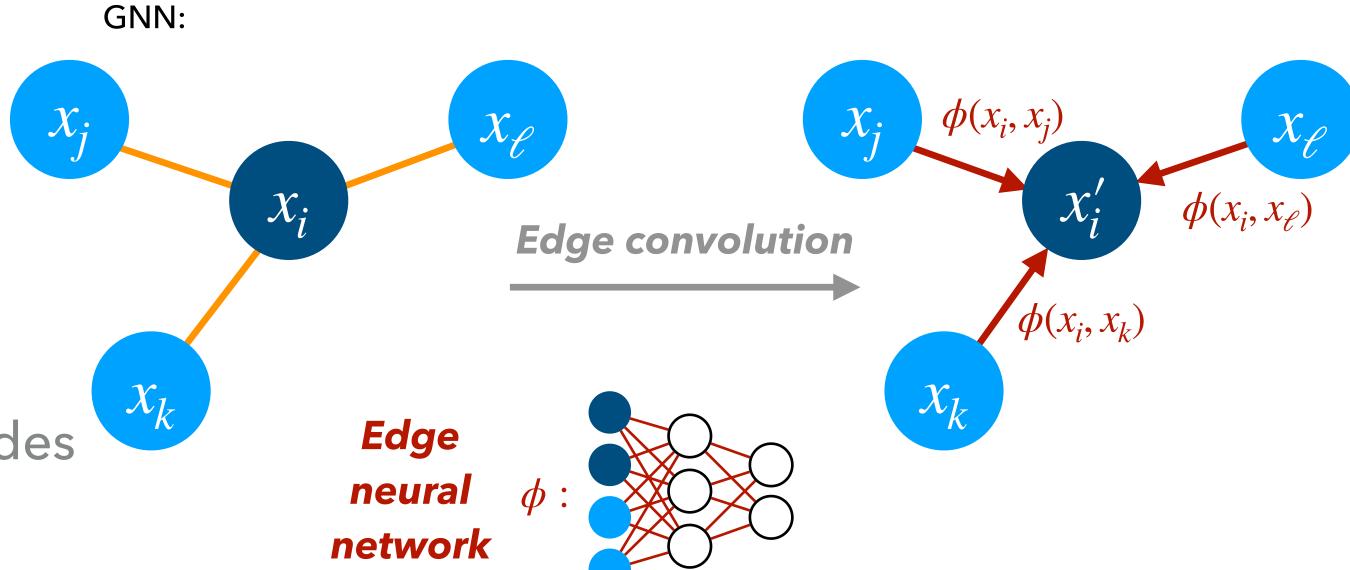




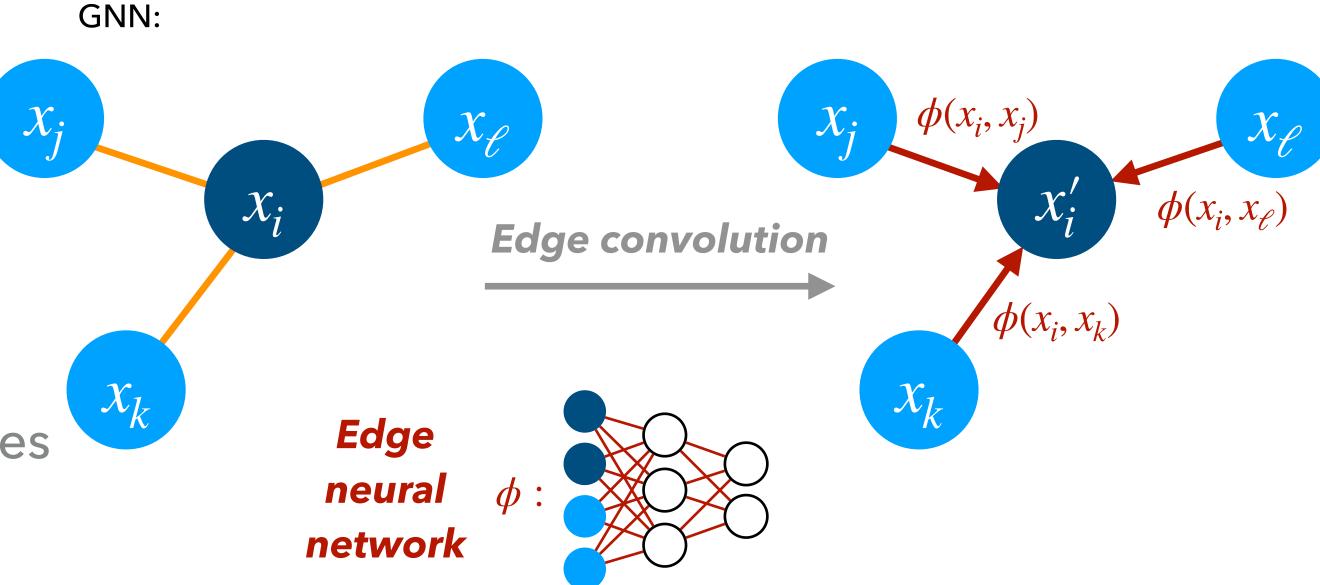
- Graph neural networks for jet tagging:
  - Each jet is treated as a graph of connected nodes (particles)



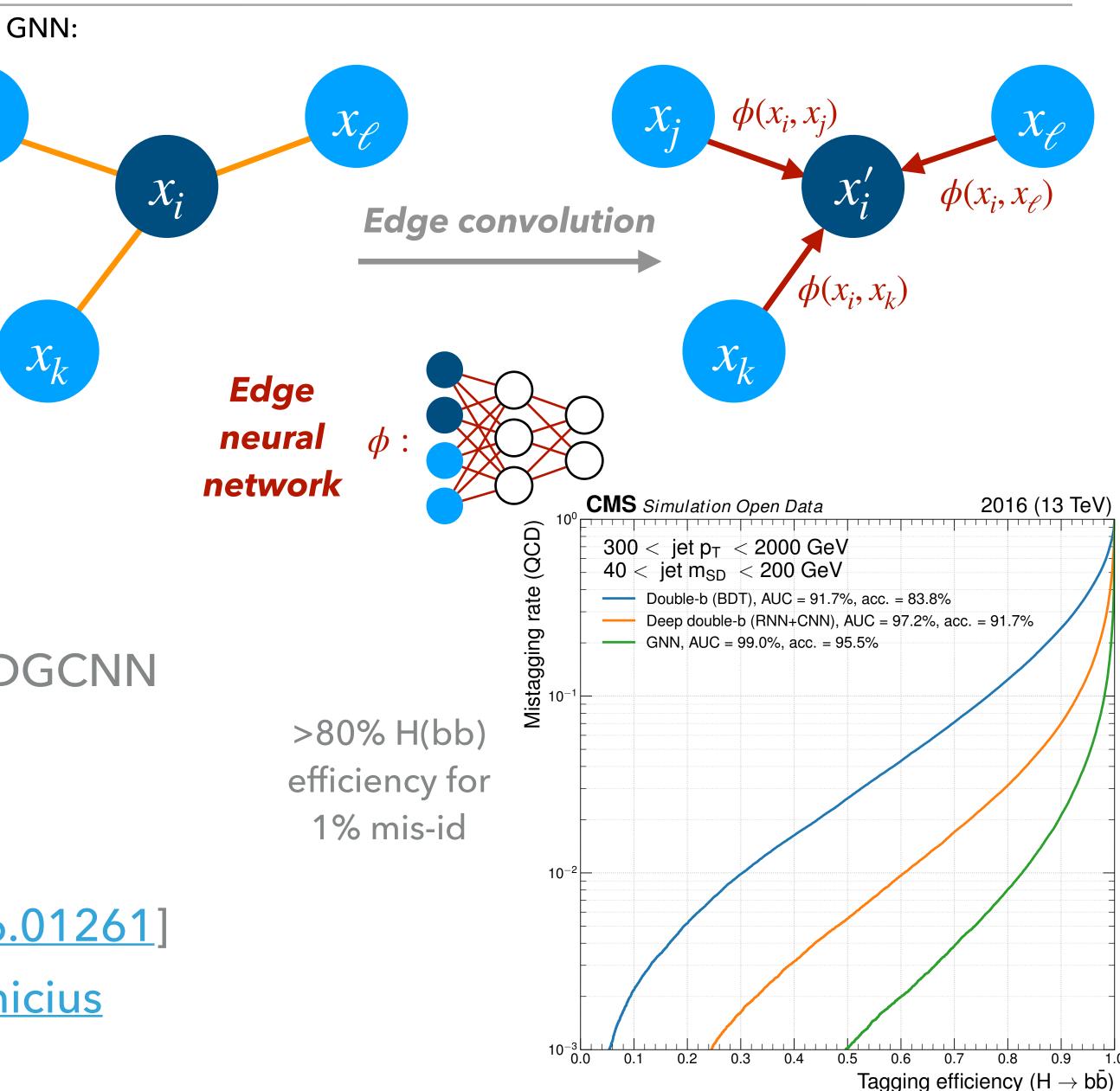
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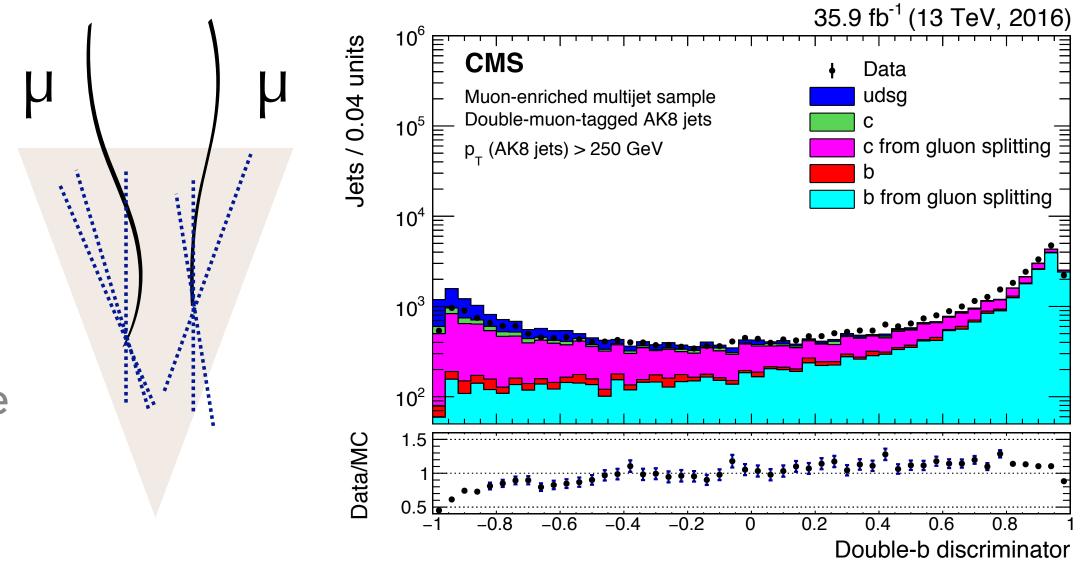


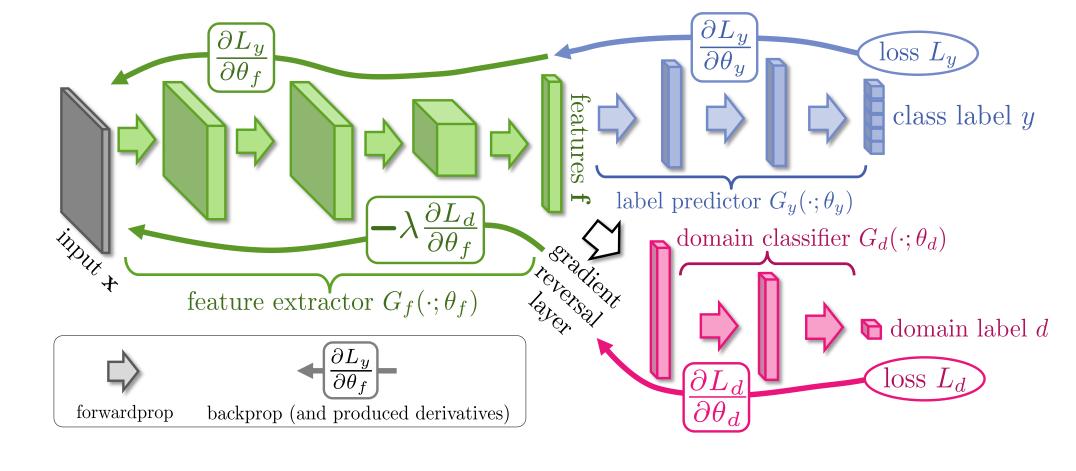
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- Examples:
  - ParticleNet [<u>arXiv:1902.08570</u>], based on DGCNN [<u>arXiv:1801.07829</u>]
  - JEDI-Net/HiggsInteractionNet
     <a href="mailto:left">[arXiv:1908.05318</a>, arXiv:1909.12285</a>],
     <a href="mailto:based-on-likeline-style="mailto:left">based on IN [arXiv:1612.00222</a>, arXiv:1806.01261
  - ▶ ABCNet [arXiv:2001.05311], see talk by Vinicius
  - ► Energy Flow Networks [<u>arXiv:1810.05165</u>]



#### EXPERIMENTAL AND ANALYSIS CONSIDERATIONS

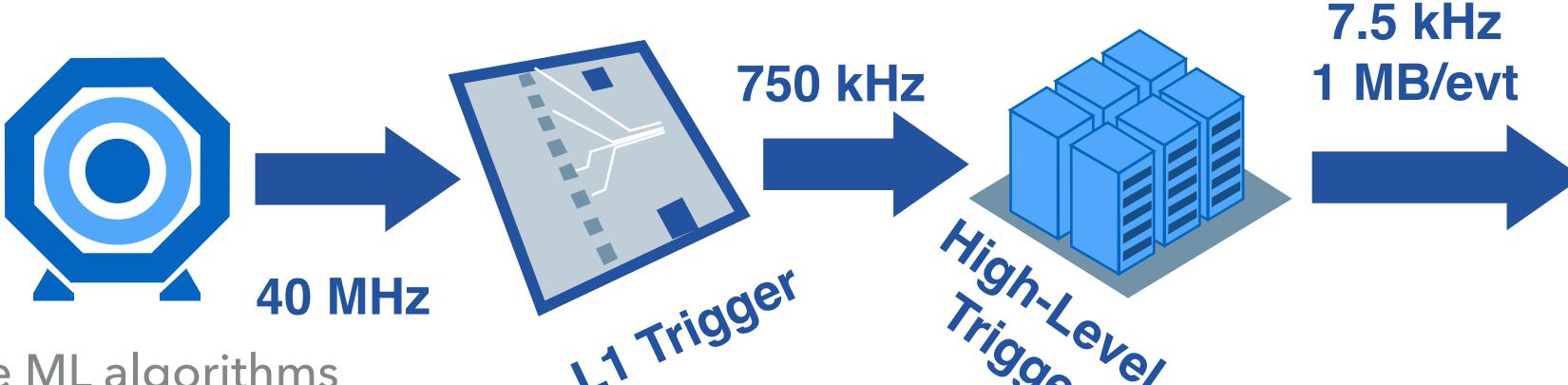
- Data/simulation correction scale factors
  - ▶ Often measured using "proxy" processes like g→bb
    - ▶ Difficult if tagger can tell g→bb and H→bb apart
    - ▶ Using Z→bb is starting to become common
  - What about cc?
    - Same concepts, but smaller rates make measurement more difficult
  - Use ML to minimize data/simulation differences [arXiv:1912.12238]
- Estimate uncertainties/resolution directly [arXiv:1912.06046]
- Decorrelation with analysis variables
  - Often want to prevent algorithm from learning aspects unconnected from the flavor element that you may use in the analysis (e.g.  $p_T$ , mass, etc.)
  - ▶ Solutions explored so far: adversarial neural networks [arXiv:1611.01046, arXiv:1409.7495], "brute force" designed decorrelated taggers (DDT) [arXiv:1603.00027], loss function penalty, training samples with varying mass and  $p_T$



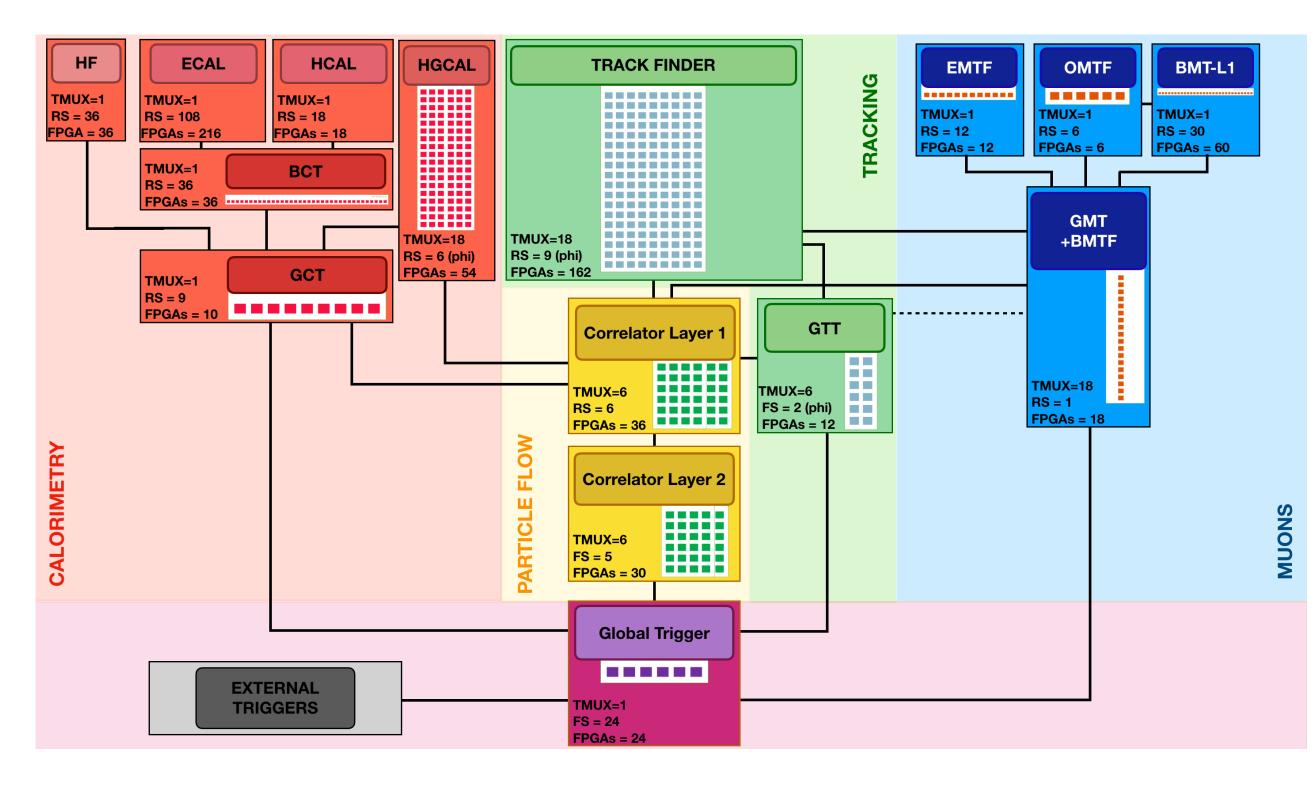


#### FLAVOR TAGGING IN THE TRIGGER

- High-level trigger
  - b-tagging algorithms available using re-optimized tracking and fast primary vertex finding



- May need ways to speed up large ML algorithms (dedicated re-training may improve perf. as well)
- Using GPUs can help (e.g. Allen in LHCb, Patatrack [arXiv:2008.13461] and SONIC in CMS [arXiv:2007.10359])
- Level-1 trigger
  - ML algorithms in FPGA firmware may be enabled with tools like <a href="https://newsre.nih.gov/hl/4">hls4ml</a>
    <a href="mailto:remain like hls4ml">[arXiv:1804.06913]</a>
  - In CMS only outer tracker will be available



#### SUMMARY AND OUTLOOK

- Heavy flavor tagging is a crucial tool for Higgs physics
- Methods have improved dramatically in recent years (and may continue to improve a bit)
  - At the same time, new issues (analysis-related, experimental, and computational) to consider
- Outlook is bright



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# BACKUB